EEG SIGNAL CLASSIFICATION FOR WHEELCHAIR CONTROL APPLICATION

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ABSTRACT

Brain–Computer Interface (BCI) requires generating control signals for external device by analyzing and processing the internal brain signal. Person with severe impairment or spinal cord injury has loss of ability to do anything. This project about the EEG signals classification for wheelchair control application. In this project, the movement of wheelchair (left, right, forward and reverse) will classified by user focusing based on four visible picture in various shape and colour also four non-visible picture (used thought image) that represent the movement. EEG signal were analyzed to find out the features by using Fast Fourier Transform (FFT). This project used alpha and beta band to collect the data. The analysis have made based on the peak and average value which then be compared to define the most significant differentiation between signals. From the result, shows that the visible colour model meet the most significant value based on the higher percentage than the other two models.

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ABSTRAK

Brain Computer Interface (BCI) memerlukan penjana isyarat kawalan untuk peranti luaran dengan menganalisis dan memproses isyarat otak dalaman. Orang yang mempunyai kecacatan teruk atau kecederaan pada saraf tunjang mempunyai kehilangan keupayaan untuk melakukan semua perkara. Projek ini berkaitan klasifikasi isyarat Electroencephalogram (EEG) untuk aplikasi kawalan kerusi roda. Berdasarkan projek ini, pergerakan kerusi roda (kiri, kanan, depan dan belakang) akan ditentukan oleh pengguna dengan memberi tumpuan kepada empat gambar yang dipaparkan dalam pelbagai bentuk dan warna dan juga empat imej maya (menggunakan imiginasi) yang mana ia mewakili pergerakan tersebut. Isyarat EEG dianalisis untuk mengetahui ciri-cirinya dengan menggunakan *Fast Fourier Transform* (FFT). Projek ini menggunakan alfa dan beta band untuk mengumpul data. Analisis ini telah dibuat berdasarkan kepada nilai puncak dan nilai purata yang kemudian dibandingkan untuk menentukan perbezaan yang paling ketara di antara isyarat . Daripada keputusan itu, menunjukkan bahawa model warna yang boleh dilihat memenuhi kreteria yang paling penting berdasarkan peratusan yang lebih tinggi berbanding model yang lain.

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LIST OF SYMBOLS AND ABBREVIATIONS

C	-	Central
F	-	Frontal
O	-	Occipital
P	-	Parietal
T	-	Temporal
T	-	Period
t	-	Time
V	-	Volt
μ	-	Mu
ω	-	Angular Frequency
H_0	-	Null Hypothesis
H_1	-	Alternative Hypothesis
Hz	-	Hertz
AEP	-	Auditory Evoked Potential
ANN	-	Artificial Neural Network
ANOVA	-	Analysis Of Variance
BCI	-	Brain-Computer Interfaces
BMI	-	Brain Machine Interface
BPS	-	Bits Per Second
CFT	-	Continuous Fourier Transform
DFT	-	Discrete Fourier Transform
DNI	-	Direct Neural Interface
ECoG	-	Electrocorticography
EEG	-	Electroencephalogram
EMG	-	Electromyographic

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EROS	-	Event-Related Optical Signal
FFT	-	Fast Fourier Transforms
FIR	-	Finite Impulse Response
FIRDA	-	Frontal Intermittent Rhythmic Delta
fMRI	-	Functional Magnetic Resonance Imaging
GUI	-	Graphical User Interface
IDFT	-	Inverse Discrete Fourier Transform
MEG	-	Magnetoencephalography
MMI	-	Mind-Machine Interface
MRI	-	Magnetic Resonance Imaging
MRS	-	Magnetic Resonance Spectroscopy
NN	-	Neural Network
OIRDA	-	Occipital Intermittent Rhythmic Delta
PCA	-	Principal Component Analysis
PET	-	Positron Emission Tomography
RF	-	Radio Frequency
SCI	-	Spinal Cord Injury
SDK	-	Software Development Kit
SMR	-	Sensory Motor Rhythm
SNR	-	Signal To Noise Ratio
SPECT	-	Single-Photon Emission Computerized Tomography
SSVEP	-	Steady State Visual Evoked Potential
STI	-	Synthetic Telepathy Interface
SVM	-	Support Vector Machine
TGC	-	Thinkgear Connector
VEP	-	Visual Evoked Potential
WT	-	Wavelet Transform

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CHAPTER I

INTRODUCTION

1.1 Project Overview

Spinal or vertebral column is the most important part in our body where the major functions are to protect the spinal cord, nerve root and also the internal organs. Spinal cord injury occurs when there is any damage to the spinal cord that blocks communication between the brain and the body. When the spinal cord injured, a person's sensory, motor and reflex messages are affected and may not be able to function as usual. The higher the level of injury, the more dysfunction can occur [1]. This may result in partial or complete paralysis of the body as well as complete paralysis of the arms and legs.

For persons with a highest level of Spinal Cord Injury (SCI), they are only able to control a muscle movement from a neck and above. To gain an independent mobility, a power electrical wheelchair with an alternative or hands free interface is crucial since normal joystick is not viable anymore. The medium can be developed by utilising information generated from eyes, tongue, voice and brainwave.

This kind of wheelchair can categorize as an intelligent wheelchair as it operate base on computer interface. The information that collected from the action of eyes, tongue, voice or brainwave then will be process to drive the movement of wheelchair to left, right, forward or reverse. The possibility of moving in an autonomous way

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gives user with severe impairment conditions a remarkable physical and psychological sense of well-being.

In recent years, it can be observed a growing of interest in Brain-Computer Interfaces (BCI) system for medical and multimedia applications. BCI is a device to provide direct interface between human brain and computer [2]. The users just need to think of movement in order to drive the system. Therefore the usage of BCI is one of the prominent devices for enabling the severe impairment user to control wheelchair.

For this project an Electroencephalogram (EEG) signal generated from single electrode that placed on the forehead will be used as a controller to initiate user-intention command. The alpha and beta band are used as the EEG device has built in chipset that detect the meditation and attention eSense. The analysis is done with sufficient EEG sample data of user focussing on four visible objects in various shapes, colours and thought image that constitute the wheelchair's movement command. Once analyzed, the model that gave highest accuracy in term of the means and variance comparison within a model will be selected as the final prototype controlling wheelchair movement via BCI.

1.2 Aim and Objectives

The aim of this project is to classify the EEG signal to control the basic wheelchair's movement which are left, right, forward and reverse. The specific objectives are:

i) To acquire and process the EEG signal from non-invasive BCI (Neurosky Mindwave) device using Matlab Software.
ii) To analyze the EEG signal in term of attention and meditation level by using their peak and average value.
iii) To classify the EEG signal into four basic movements based on various visible and non visible user- input representations.
iv) To select the best between shapes', colours' and thought image's model for wheelchair control application.

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1.3 Problem Statement

Every year, around the world, between 250 000 and 500 000 people suffer a spinal cord injury (SCI) and severe impairments. The majority of spinal cord injuries are due to preventable causes such as road traffic crashes, falls or violence [3]. The damage of spinal cord and nerve root may effect from incomplete to total dysfunction. Conventionally, most people with severe impairments conditions are unable to control their electrical wheelchair using a standard joystick. A complete paralysis of the body severe impairment people as well as complete paralysis of the arms and legs cause the power wheelchair with alternative interface is needed. Limited physical movement above the fourth cervical vertebra typically no single alternative interface provides a comprehensive solution to the control wheelchair. Therefore this project will develop the BCI system based on EEG signal classification to control wheelchair so that the patients can use their brain to move the wheelchair without any assistant.

1.4 Scope

The scopes of this study are:

i) Use the Neurosky Mindwave of single electrode EEG headset to capture the brain signal.
ii) Constraint of four basic wheelchair's movement which are left, right, forward and reverse.
iii) Use Matlab software to analyse the collected data.

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CHAPTER 2

LITERATURE REVIEW

In this chapter, there are two main subtopics will be discussed which are theoretical study and previous works that related to this project. The former will be discussing on some related theories and the explanation on each component used in this project while the latter is review recent works that related to this project to make better understanding in term of the procedure and technique used in each successful projects.

2.1 Theoretical study

The theoretical study discussed about the study of the Brain Computer Interface system including the types of device, electrode channel and the signal acquisition.

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2.1.1 Brain Computer Interface (BCI)

A Brain Computer Interface (BCI) often called a Mind-Machine Interface (MMI) or sometimes called a Direct Neural Interface (DNI), Synthetic Telepathy Interface (STI) or a Brain Machine Interface (BMI) is a direct communication pathway between the brain and an external device. BCIs are often directed at assisting, augmenting or repairing human cognitive or sensory-motor functions [4].

Humans' brain is filled with neurons, individual nerve cells connected to one another by dendrites and axons. Every action like think, move, feel or remember something make neurons are at work. That work is carried out by small electric signals that zip from neuron to neuron as fast as 250 mph [5]. The signals are generated based on the differences in electric potential carried by ions on the membrane of each neuron. The signals then can be detected, interpreted to what they mean and use them to direct a device of some purpose.

Therefore, BCI is a system that provides direct interface between the human brain and the computer [2]. In order to develop the BCI system, the feasible technique should be studied. BCI systems are broadly classified into invasive and non-invasive techniques.

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2.1.1.1 Invasive BCI

Invasive BCI are Neuroprosthetics where electrode arrays heads are buried within the brain during neurosurgery and left there on a permanent basis. Invasive devices produce the highest quality signals of BCI device because they lie in the grey matter of brain. They have by far the best signal to noise ratio and accuracy of any BCI method. Unfortunately invasive BCI is costly and require complex surgery to implant. They are require a permanent hole in the skull, build-up prone to scar-tissue, causing the signal to become weaker or even non-existent, as the body reacts to a foreign object in the brain.

Electrocorticography (ECoG) is one of the invasive BCI. It also known as partially invasive as the device is implanted inside the skull but rest outside the brain rather than within the grey matter. ECoG is a very promising intermediate BCI modality because it has higher spatial resolution, better signal-to-noise ratio, wider frequency range, and less training requirements than scalp-recorded EEG, and at the same time has lower technical difficulty, lower clinical risk, and probably superior long-term stability than intracortical single-neuron recording [6]. This feature profile shows potential for real world application for people with motor disabilities. Unfortunately ECoG is also costly and required dangerous nature of surgeries for such system. Figure 2.1 shows the 8x8 electrode grid that place on the brain surface.

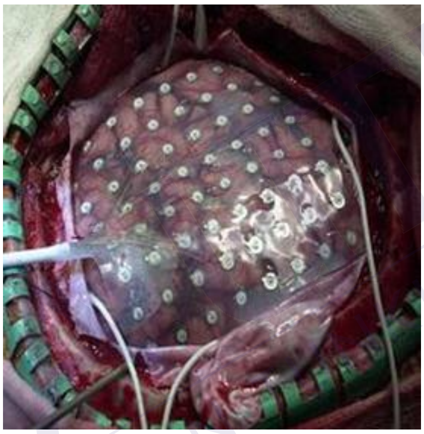

Figure 2.1: 8x8 of Electrode Grid Placing On the Surface of Brain

2.1.1.2 Non-Invasive BCI

Non-invasive BCI is the most popular technique where the electrodes need to be placed outside of the skull or on the scalp. Non-invasive methods are limited in that they are often susceptible to noise, have worse signal resolution due to distance from the brain, and have difficulty recording the inner workings of the brain [7]. However they have the advantages that can combat these difficulties by lower cost, greater portability and the fact that they do not require any special surgery.

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Most non-invasive BCI systems use electroencephalogram (EEG) signals. EEG is the first non-invasive neuron imaging technique discovered which is used for measuring the electrical activity of the brain. Besides electrical activity, neural activity also produces other types of signals such as magnetic and metabolic that could be used in a BCI. Magnetic fields can be recorded by using magnetoencephalography (MEG), while brain metabolic activity which is reflected in changes in blood flow can be observed by using positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging [8].

Unfortunately, such alternative techniques require sophisticated devices that can be operated only in special facilities. Moreover, techniques for measuring blood flow have long latencies and thus are less appropriate for interaction [8].

2.1.2 Electroencephalography (EEG)

EEG is the first non-invasive neuron imaging technique discovered which is used for measuring the electrical activity of the brain. EEG signals are detected from the scalp and contain noise as a result of electrical interference and movement of electrodes [9]. Applying a large number of EEG channels may include noisy and redundant signals that degrade the BCI performance and also involve a prolonged preparation time that directly impacts the convenience in the use of the BCI. Therefore, selecting the least number of channels that yield the best or required accuracy can balance both needs for performance and convenience [10]. Due to its ease of use, cost and high temporal resolution this method is the most widely used one in BCIs nowadays [11].

The advantages of using EEG technique are:

a) Hardware costs are significantly lower than those of most other techniques.
b) EEG sensors can be used in more places than fMRI, SPECT, PET, MRS, or MEG, as these techniques require bulky and immobile equipment. For example, MEG requires equipment consisting of liquid helium-cooled detectors that can be used only in magnetically shielded rooms,

altogether costing upwards of several million dollars and fMRI requires the use of a 1-ton magnet in, again, a shielded room.

c) EEG has very high temporal resolution, on the order of milliseconds rather than seconds. EEG is commonly recorded at sampling rates between 250 and 2000 Hz in clinical and research settings, but modern EEG data collection systems are capable of recording at sampling rates above 20,000 Hz if desired. MEG and EROS are the only other non-invasive cognitive neuroscience techniques that acquire data at this level of temporal resolution.

d) EEG is silent, which allows for better study of the responses to auditory stimuli.

e) EEG does not aggravate claustrophobia, unlike fMRI, PET, MRS, SPECT, and sometimes MEG.

f) EEG does not involve exposure to high-intensity (>1 Tesla) magnetic fields, as in some of the other techniques, especially MRI and MRS. These can cause a variety of undesirable issues with the data, and also prohibit use of these techniques with participants that have metal implants in their body, such as metal-containing pacemakers.

g) Extremely non-invasive, unlike ECoG which actually requires electrodes to be placed on the surface of the brain.

The characteristics of EEG that compare favorably with behavioral testing:

a) EEG can detect covert processing (i.e., processing that does not require a response)

b) EEG can be used in subjects who are incapable of making a motor response.

c) EEG is a powerful tool for tracking brain changes during different phases of life. EEG sleep analysis can indicate significant aspects of the timing of brain development, including evaluating adolescent brain maturation.

h) In EEG there is a better understanding of what signal is measured as compared to other research techniques, i.e. the BOLD response in MRI.

2.1.3 EEG Electrode Brain Channel

Typically, in BCI study, electrode locations are selected arbitrarily from scalp area corresponding to the motor cortical region to record the electrical activity of the brain. It is well known that the variation of the surface potential distribution on the scalp reflects functional activities emerging from the underlying brain [12]. This surface potential variation then can be record and the voltage of electrodes can be measure, which are then filter, amplify, and record.

Electrodes conduct voltage potentials as microvolt level signals, and carry them into amplifiers that magnify the signals approximately ten thousand times. The use of this technology depends strongly on the electrodes positioning and the electrodes contact [12]. For this reason, electrodes are usually constructed from conductive materials, such as gold or silver chloride including a conductive gel that will apply between electrode and scalp to maintain an acceptable signal to noise ratio. The gel based electrode system however have difficulties on the need of long montage time and the need to wash the user's hair after the recording. Therefore, the dry electrode system will be use to reduce the electrode- skin impedance.

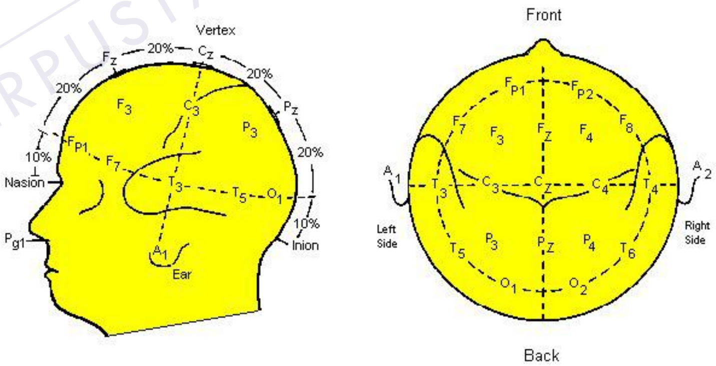

Figure 2.2: The International 10/20 Systems of Electrode Placement

Figure 2.2 shows the location of electrode according to International 10/20 System. Each site has a letter to identify the lobe and a number or another letter to identify the hemisphere location. The letters F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal and Occipital. Even numbers (2, 4, 6, 8) refer to the right

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hemisphere and odd numbers (1, 3, 5, 7) refer to the left hemisphere. The z refers to an electrode placed on the midline.

2.1.4 Data Acquisition

Nowadays, for the data acquisition, there are many commercial options for EEG headsets and head-caps. Single electrode headsets, such as the Neurosky Mindwave, were inexpensive and simple. Most devices had an accessible Software Development Kit (SDK) so development would be relatively simple. Figure 2.3 shows an illustration of all of the options for data acquisition devices. All devices performed essentially the same but the big differences from option to option are the size, power, and cost of the actuator.

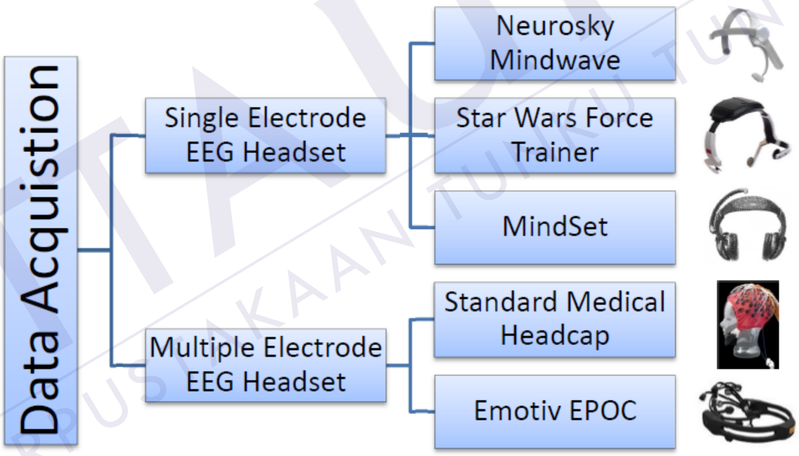

Figure 2.3: Data Acquisition Design Option

NeuroSky technology allows for low-cost EEG-linked research and products by using inexpensive dry sensors rather than older EEGs require the application of a conductive gel between the sensors and the head. The systems also include built-in electrical noise reduction software/hardware, and utilize embedded (chip level) solutions for signal processing and output [14]. The dry electrodes can measure brainwaves millimetres from the scalp and thus can easily be worn over hair. These sensors are a significant technological breakthrough in that they are the only non-contact EEG sensors ever developed.

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Mindwave(MW003) Mindwave(MW001)

Figure 2.4 : Neurosky Mindwave Mobile

Figure 2.4 shows the Neurosky Mindwave, the product of NeuroSky Technology that can be used for data acquisition. Mindwave (MW001) is the device that uses RF system to function. This device comes with RF adapter in order to transmit the EEG signal to computer. The Mindwave (MW003) is the device that uses the bluetooth system to transfer the EEG signals. It can be pair to any devices that have built in Bluetooth system such as computer, Smartphone, and tablet which is can run the Neurosky Mindwave application. This device safely measures and outputs the EEG power spectrums like alpha waves, beta waves, etc. It has embedded with attention and meditation meters and also eye blinks detection.

The entire signal can be capture as there has ThinkGear Connector (TGC) which is runs as a background process on the computer and is responsible for directing the mindwave headset data from the serial port to an open network socket.

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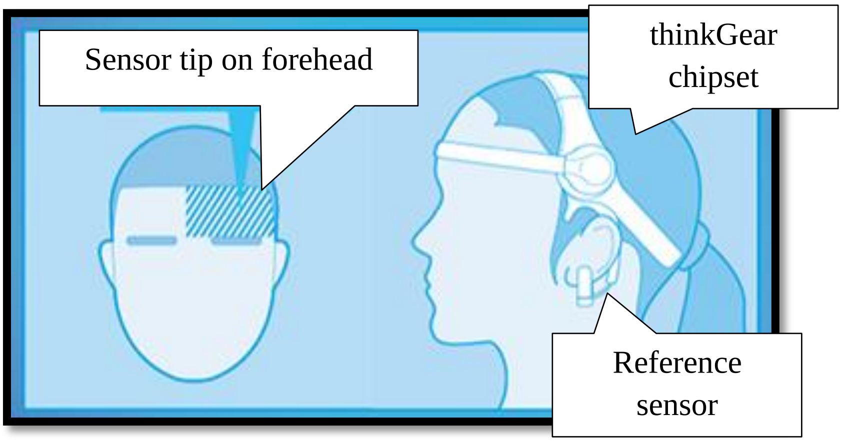

Figure 2.5: The Technique To Put On Neurosky Mindwave (Neurosky,2011)

Figure 2.5 shows the location to place the Neurosky Mindwave. This device used a single channel dry electrode which is on the sensor arm, place on the forehead above the eye (FP1 position) while used the ear clip as a ground.

2.1.5 Features of EEG Signal

The EEG signal is typically described in terms of rhythmic activity and transients. The rhythmic activity is divided waves into bands by frequency while the transient is referring to spike and sharp waves. To some degree of rhythmic activity, these frequency bands are a matter of classification but these designations occur because rhythmic activity within a certain frequency range was noted to have a certain distribution over the scalp or a certain biological significance. There are five types mostly important.

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2.1.5.1 DELTA

Delta waves lie within the range of 0.5 to 4 Hz, with variable amplitudes. It tends to be the highest in amplitude and the slowest waves. Delta waves are generally associated with slow wave sleep (during stages 3 and 4 of the stage of sleep). These brain wave are primarily associated with deep sleep, and in the waking state, were thought to15 indicate physical defects in the brain.

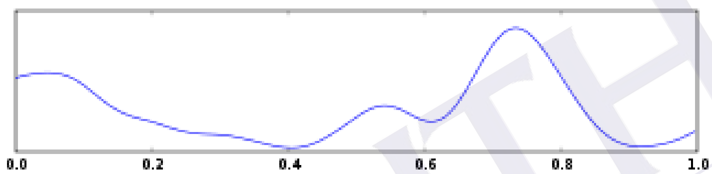

Figure 2.6: Delta Wave Pattern

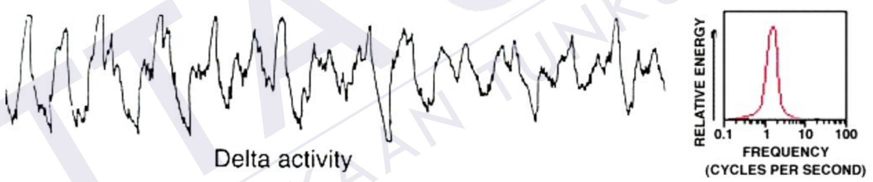

Figure 2.7: Delta wave in Time Domain and Frequency Domain

It is usually most prominent frontally in adults (e.g. FIRDA - Frontal Intermittent Rhythmic Delta) and posterior in children (e.g. OIRDA - Occipital Intermittent Rhythmic Delta).

2.1.5.2 THETA

Theta waves lie within the range of 4 to 8 Hz, with an amplitude usually greater than 20µV. Theta arises from emotional stress, especially frustration or disappointment. Theta has been also associated with access to unconscious material, creative inspiration and deep meditation. The large dominant peak of the theta waves is around 7 Hz.

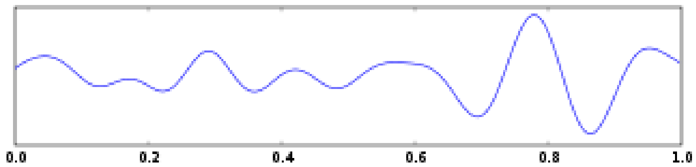

Figure 2.8: Theta Wave Pattern

Figure 2.9: Theta wave in Time Domain and Frequency Domain

2.1.5.3 ALPHA

The rate of change lies between 8 and 13 Hz, with 30-50µV amplitude. Alpha waves have been thought to indicate both a relaxed awareness and also in attention. Alpha alone seems to indicate an empty mind rather than a relaxed one, a mindless state rather than a passive one, and can be reduced or eliminated by opening the eyes, by hearing unfamiliar sounds, or by anxiety or mental concentration. They are strongest over the occipital (back of the head) cortex and also over frontal cortex. Alpha is the most prominent wave in the whole realm of brain activity and possibly covers a greater range than has been previously thought of. It is frequent to see a peak in the beta range as high as 20 Hz, which has the characteristics of an alpha state rather than a beta, and the setting in which such a response appears also leads to the same conclusion.

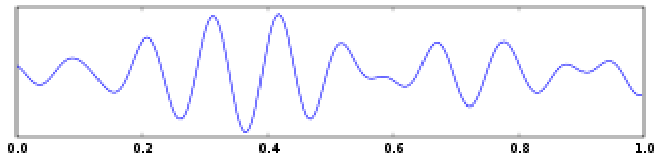

Figure 2.10: Alpha Wave Pattern

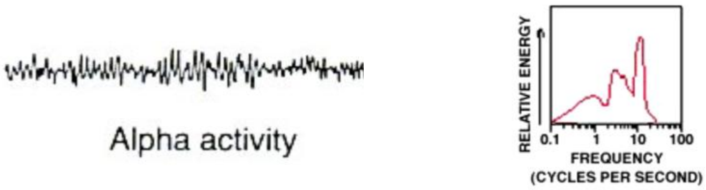

Figure 2.11: Alpha wave in Time Domain and Frequency Domain

2.1.5.4 BETA

The rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30µV. Beta activity is closely linked to motor behavior and is generally attenuated during active movements like active thinking, active attention, and focus on the outside world or solving concrete problems. It can reach frequencies near 50 Hz during intense mental activity. Rhythmic beta with a dominant set of frequencies is associated with various pathologies and drug effects, especially benzodiazepines. It may be absent or reduced in areas of cortical damage. It is the dominant rhythm in patients who are alert or anxious or who have their eyes open.

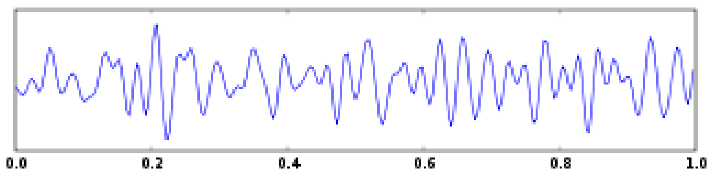

Figure 2.12: Beta Wave Pattern

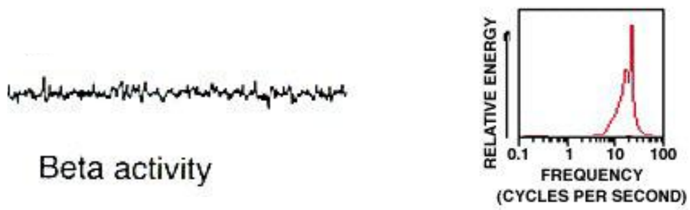

Figure 2.13: Beta wave in Time Domain and Frequency Domain

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2.1.5.5 GAMMA

Gamma waves lie within the range of 35Hz and above. It is thought that this band reflects the mechanism of consciousness - represent binding of different populations of neurons together into a network for the purpose of carrying out a certain cognitive or motor function. (Feeding back on themselves over time to create a sense of stream-of-consciousness).

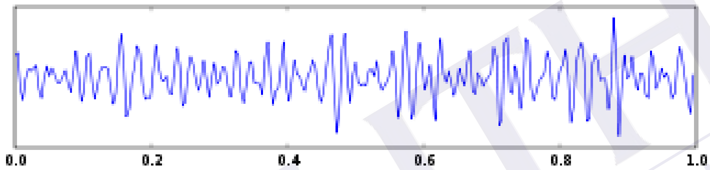

Figure 2.14: Gamma Wave Pattern

2.1.5.6 MU (μ)

Mu ranges 8–12 Hz and partly overlaps with other frequencies. It is spontaneous EEG wave associated with motor activities and maximally recorded over motor cortex. It reflects the synchronous firing of motor neurons in rest state. They diminish with movement or the intention to move. Mu wave is in the same frequency band as in the alpha wave but this last one is recorded over occipital cortex.

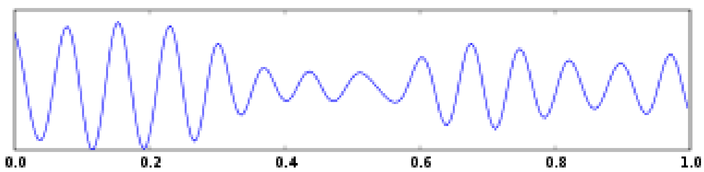

Figure 2.15: MU Wave Pattern

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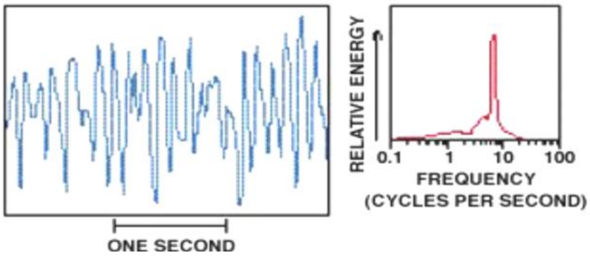

Figure 2.16: Mu wave in Time Domain and Frequency Domain

Most attempt to control a computer with continuous EEG measurements work by monitoring Alpha or Mu waves, because people can learn to change the amplitude of these two waves by making the appropriate mental effort. A person might accomplish this result, for instance, by recalling some strongly stimulating image or by raising his or her level of attention [13]. The normal EEG varies by age. The neonatal EEG is quite different from the adult EEG. The EEG in childhood generally has slower frequency oscillations than the adult EEG.

2.1.6 NeuroSky eSense Meter

ESense Attention meter indicates the intensity of a user's level of mental focus or concentration while eSense Meditation meter indicates the level of a user's mental calmness or relaxation. Note that Meditation is a measure of a person's mental levels, not physical levels, so simply relaxing all the muscles of the body may not immediately result in a heightened Meditation level. However, for most people in most normal circumstances, relaxing the body often helps the mind to relax as well. Meditation is related to reduce activity by the active mental processes in the brain, and it has long been an observed effect that closing one's eyes turns off the mental activities which process images from the eyes, so closing the eyes is often an effective method for increasing the Meditation meter level. Distractions, wandering thoughts, anxiety, agitation, and sensory stimuli may lower the Attention and Meditation meter levels.

A relative eSense scale is 1 to 100. On this scale, a value between 40 to 60 at any given moment in time is considered "neutral", and is similar in notion to "baselines" that are established in conventional EEG measurement techniques (though the method for determining a ThinkGear baseline is proprietary and may differ from conventional EEG). A value from 60 to 80 is considered "slightly elevated", and may be interpreted as levels being possibly higher than normal (levels of Attention or Meditation that may be higher than normal for a given person). Values from 80 to 100 are considered "elevated", meaning they are strongly indicative of heightened levels of that eSense.

Similarly, on the other end of the scale, a value between 20 to 40 indicates "reduced" levels of the eSense, while a value between 1 to 20 indicates "strongly lowered" levels of the eSense. These levels may indicate states of distraction, agitation, or abnormality, according to the opposite of each eSense. An eSense meter value of 0 is a special value indicating the ThinkGear is unable to calculate an eSense level with a reasonable amount of reliability. This may be (and usually is) due to excessive noise as described in the POOR_SIGNAL Quality section above.

The reason for the somewhat wide ranges for each interpretation is that some parts of the eSense algorithm are dynamically learning, and at times employ some "slow-adaptive" algorithms to adjust to natural fluctuations and trends of each user, accounting for and compensating for the fact that EEG in the human brain is subject to normal ranges of variance and fluctuation. This is part of the reason why ThinkGear sensors are able to operate on a wide range of individuals under an extremely wide range of personal and environmental conditions while still giving good accuracy and reliability. Developers are encouraged to further interpret and adapt these guideline ranges to be fine-tuned for their application (as one example, an application could disregard values below 60 and only react to values between 60-100, interpreting them as the onset of heightened attention levels).

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2.1.7 EEG Signal Classification Tools

MATLAB software provides tools to acquire, analyze, and visualize data, enable to gain insight into the data in a fraction of the time using spreadsheets or traditional programming languages. The data from hardware devices, such as computer's serial port or sound card, as well as stream live can be acquire and measure directly into MATLAB for analysis and visualization by using MATLAB with add-on products such as Neurosky Mindwave. This software also can communicate with instruments such as oscilloscopes, function generators, and signal analyzers.

Furthermore, MATLAB enable to manage, filter, and pre-process data. MATLAB provides functions for filtering and smoothing, interpolation, convolution, and fast Fourier transforms (FFTs). It also can perform exploratory data analysis to uncover trends, test assumptions, and build descriptive models such as using Neural Network.

2.2 Previous Works

This previous works are discussed about the paper that related to this project in term of their devices, tools for data analyzing and technique used.

2.2.1 Brain Computer Interface (BCI)

Brain Computer Interface (BCI) systems are broadly classified into invasive and non-invasive techniques. Theoretically, the invasive BCI need the surgical performance to implant the electrode to grey matter of brain and it will result by produce the highest quality signals of BCI device.

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2.2.1.1 **Methods Towards Invasive Human Brain Computer Interfaces**

In their paper, Thomas Navin Lal.*et.al* (2005) researched about the Methods Towards Invasive Human Brain Computer Interfaces to investigate if BCIs based on electrocorticography (ECoG) are a viable alternative. Most human BCIs are based on extracranial electroencephalography (EEG). One reason for this is the low signal-to-noise ratio of the EEG [14].

The paper presented the method and used examples of intracranial EEG recordings of three epilepsy patients with electrode grids placed on the motor cortex. The system then allows its users to write text on the screen of a computer or to surf the web. Most of the patient cannot concentrate for a long period of time cause by the surgery effect so only few data were collected. For data analysis, researcher used a Support Vector Machine (SVM) to train iterations and analyzed its weight vector. The feature that corresponds to the smallest weight vector entry is removed. Result shows that the error rate range is still high compared to intracranial EEG. They believe that the tasks that work well for extracranial EEG are not ideal for ECoG.

2.2.1.2 **Design Of A Brain Computer Interface System Based On Electroencephalogram (EEG)**

Nowadays, the non-invasive BCI based on EEG are normally used for many applications especially in medical and multimedia application. Ozan Gunaydin, Mehmed Ozkanwas (2013) developed and implemented a low power EEG based brain computer interface to classify the pattern of motor imagery task into one of two classes: right hand or left hand movement [15].

This paper chose the data acquisition of mu and beta frequency has for features extraction. Three different methods of features extraction were used such Discrete Wavelet Transform, Power Spectrum Analysis and Band Pass FIR filters. Two different feature extraction methods were evaluated in Matlab applying db10 level4 Discrete Wavelet Transform and FFT transform for feature extraction. After getting the results, as the second phase, for implementation with a microcontroller a resource efficient method was developed which FIR band pass filters utilized instead of Wavelet transform to extract sub band information. These features were used as inputs to a two layer feed forward back propagation neural network for classification. Designed system was trained and simulated with the data provided in BCI Competition II. With the direction of the results, a low power system with the TI MSP430 microcontroller using FIR filters and a neural network was implemented.

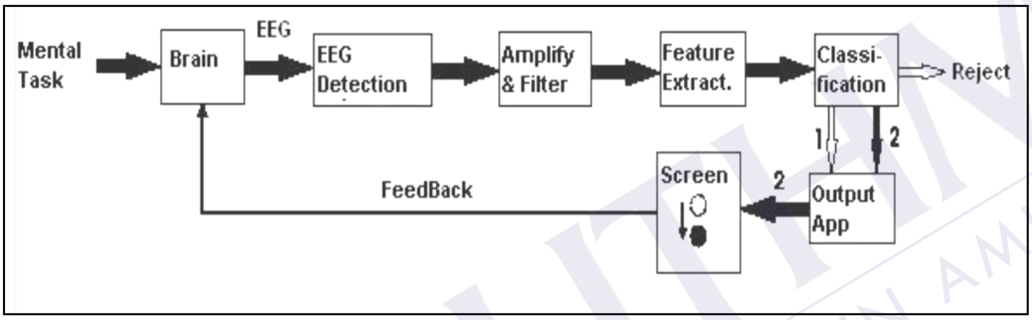

Figure 2.17: A Typical Brain Computer Interface System. Cursor Control, Bio-Feedback or Control of a Robot Arm is Examples of Output Applications.

2.2.1.3 <u>A Brain Computer Interface for Smart Home Control</u>

Lee.W.T, Nisar.H, Malik.A.S, Kim Ho Yeap (2013) had developed a thought controlled smart home system using a non invasive brain computer interface (BCI). The Electroencephalographic (EEG) signals recorded from the brain activity using the Emotiv EPOCH headset where interfaced with the help of mouse emulator to a graphical user interface (GUI) on the computer screen. The user will use this GUI to control various devices in a smart home. The user will select his desired application using a raise of an eyebrow (or a smirk, or a combination of actions if needed and to increase the sensitivity of the system), that will cause a mouse click on the desired control; as a result the control will be toggle [17].

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2.2.2 Features Extraction and Classification Method

The raw data signals that captured from the brain were in time domain. Time domain analysis is mainly based on the voltage – time plot or current – time plot. In time domain analysis, the variable is always measured against time. In order to extract the features which are separated by bands of frequency, the method for conversion of time domain into frequency domain should be applied. The features then will train and test to get the signal classification.

2.2.2.1 A Brain Computer Interface Based on FFT and Multilayer Neural Network - Feature Extraction and Generalization

Kenji Nakayama, Yasuaki Kaneda and Akihiro Hirano (2007) [19] had been worked on BCI feature extraction and generalization by FFT and multilayer Neural Network. In this paper, a multilayer neural network is applied to BCI, which is one of hopeful interface technologies between humans and machines. Amplitude of the FFT of the brain waves is used for the input data. Several techniques have been introduced for pre-processing the brain waves. They include segmentation along the time axis for fast response, nonlinear normalization to emphasize important information, averaging samples of the brain waves to suppress noise effects and reduction in the number of the samples to realize a small size network.

This paper used a multilayer neural network having a single hidden layer. In the testing phase, the maximum output becomes the winner and the corresponding mental task is assigned. However, when the winner has small value, estimation becomes incorrect. Therefore, the answer of the neural network is rejected, that is any mental task cannot be estimated. The error back-propagation algorithm is employed for adjusting the connection weights. Two kinds of generalization techniques, including adding small random noises to the input data and decaying connection weight magnitude, are applied. The simulation was carried out and the accuracy was improved.

2.2.2.2 Investigating Advantages And Disadvantages Of The Analysis Of A Geometrical Surface Structure With The Use Of Fourier And Wavelet Transform

Stanisław Adamczak, Włodzimierz Makieła and Krzysztof Stępień (2010) [20] investigated about the advantages and disadvantages between Fast Fourier Transform and Wavelet Transform. This paper discussed that The Fourier transform is extremely useful when analyzing periodic signals. Therefore it is a very useful tool for evaluation of roundness or cylindricity profiles. It usually allows obtaining accurate information on the analyzed surface. Wavelet transform does not provide such accurate information. However, because it is well localized in the time and frequency domains it can detect irregularities of the profile such as cracks or scratches of the surfaces. Wavelet transform is also a very convenient tool for demonising the measuring signal.

2.2.2.3 EEG Signal Processing For Controlling a Robotic Arm

Howida A.Shedeed, Mohamed F.Issa and Salah M.El-Sayed (2013) had utilized the technique of Wavelet Transform (WT), Fast Fourier Transform (FFT) and Principal Component Analysis (PCA) to extract features for the project of Brain EEG Signal Processing for Controlling a Robotic Arm. EEG signals associated with 3 arm movements (close, open arm and close hand) [18]. Classification rates of 91.1%, 86.7% and 85.6% were achieved with the three used features extraction techniques respectively. Multi-layer Perceptron Neural Network trained by a standard back propagation algorithm was used for classifying the three considered tasks.

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2.2.2.4 EEG Signal Classification using Principal Component Analysis with Neural Network in Brain Computer Interface Applications

Classification method should be applied to the set of extracted features to acquire a final model of analysis. Kottaimalai R, Pallikonda Rajasekaran M, Selvam V and Kannapiran B (2013)[21] presented an Artificial Neural Network (ANN) which is a functional pattern classification technique, trained all the way through the error Back Propagation algorithm.

In this paper, in order to classify the mental tasks, the brain signals are trained using neural network and also using Principal Component Analysis (PCA) with Artificial Neural Network. PCA is use to eliminate the redundant data in the dataset while Neural Network (NN) use as data trainer. During the classification of the mental tasks using Neural Network classifier, the data is misclassified at the output where the percentage of correct classification is low. Similarly during the classification of the mental tasks using Principal Component Analysis with Neural Network classifier, the data is perfectly classified at the output. The percentage of correct classification is good because of the reduction of the redundant variables in the dataset. Finally it is observed that the correctly classified percentage of data is better in Principal Component Analysis with Neural Network compared to Neural Network alone.

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